Computers & Industrial Engineering 142 (2020) 106333

Contents lists available at ScienceDirect

Computers & Industrial Engineering

journal homepage: www.elsevier.com/locate/caie

Cyber-physical systems for performance monitoring in production intralogistics

O. Mörth[a], Christos Emmanouilidis[b,*], N. Hafner[a], M. Schadler[a]

[a] Graz University of Technology, Austria
[b] Cranfield University, United Kingdom

ARTICLE INFO

Keywords:
Cyber-physical systems
Intralogistics
Internet of things
Context awareness
Data value chain
Performance monitoring

ABSTRACT

The realization of a higher business value in manufacturing requires optimized internal logistics systems in terms of operational performance, uptime and sustainability. This paper deals with the introduction of Internet of Things (IoT) to unlock new capabilities for enhancing the performance of intralogistics. Specifically, it introduces a design perspective for IoT-driven analytics in intralogistics, within a Cyber-Physical Systems (CPS) approach. Such an approach enables the creation of data process chains linked to performance measurement for intralogistics, a prerequisite for optimizing logistics operations within production environments. An overview of key performance indicators for this domain is offered, followed by an outline of recent research on IoT and CPS and the role of context information management for IoT-enabled data process chains. The conceptual model is illustrated through a representative use case of a CPS demonstrator for performance monitoring in intralogistics. The application implements a simple data process chain, starting from the acquisition and processing of data from a conveyor testbed, followed by the determination and visualization of appropriate performance monitoring information on a dashboard.

1. Introduction

Production management activities, ranging from sourcing raw materials all the way to delivering finished goods to customers, need to jointly optimize manufacturing and logistics operations. While general logistics comprises all necessary transport activities, intralogistics is only focused on the internal transport of goods within the physical limits of a single enterprise. The realization of benefits and thus, delivery of a higher business value, requires optimized internal logistics systems in terms of operational performance, uptime and sustainability (Bode & Preuß, 2005; Gudehus & Kotzab, 2012). Automation plays a key role in improving internal logistics systems (Granlund & Wiktorsson, 2014). While identification and sortation processes have already reached a high degree of automation, other tasks, such as un-/loading, singulation and commissioning, are still performed largely manually (Granlund & Wiktorsson, 2014; Fritz, 2016). However, automation in intralogistics also brings challenges, such as the need for higher skilled human operators to handle the technology properly (Granlund & Wiktorsson, 2014). Furthermore, as current internal logistics systems are already very complex, the abilities of human operators to understand, manage, and optimize their performance have reached their limits (Gilchrist, 2016).

New approaches, enabled by the Internet of Things (IoT), can establish enhanced connectivity across the internal logistics system infrastructure. Such connectivity upgrades the capabilities for collecting data relevant to mapping the state of individual subsystems and of the internal logistics system as a whole. This allows to monitor and analyze the operating performance of intralogistics, which is a prerequisite for making more informed choices regarding its management and optimization (Macaulay, Buckalew, & Chung, 2015). Leveraging upon such capabilities, the implementation of Cyber-Physical Systems (CPS) brings together the benefits of connectivity and interaction. This allows determining contextually relevant information as well as communicating key performance indicators (KPIs) in visual ways through appropriate dashboards (Scholze & Barata, 2016). Analyzing such distilled information enables gaining insight and potentially new knowledge to drive optimizing internal logistics systems in a way that is much harder for traditional methods to match. A higher transparency of the operating performance results in better informed decision-making (Gilchrist, 2016). Furthermore, context-aware computing enables the reduction of the complexity of data communicated to operators, through filtering only the information contextually relevant to the characteristics of specific situations. Analyzing this contextual information makes it possible to tailor intervention actions to the specific

* Corresponding author.
E-mail address: christosem@ieee.org (C. Emmanouilidis).

https://doi.org/10.1016/j.cie.2020.106333

Available online 01 February 2020

circumstances under consideration (Perera, Zaslavsky, Christen, & Georgakopoulos, 2014). This potential is not yet sufficiently exploited towards optimizing internal logistics systems. Aiming to address such needs, this paper introduces a design perspective for IoT-driven analytics in intralogistics. A representative use case is offered through the development of a CPS demonstrator for performance monitoring in intralogistics. The developed application implements a simple data process chain, starting with the acquisition and processing of data from a conveyor testbed, followed by the determination and visualization of performance monitoring information on a dashboard.

The rest of the paper is structured as follows. Section 2 outlines related work highlighting current needs, opportunities, and challenges. Section 3 introduces the concept of a CPS in intralogistics and context categories for this application domain. The development of a CPS demonstrator is presented in Section 4, including the design approach, the implementation, as well as indicative testing and results. The paper concludes with a discussion and summary of the main contributions, including pointers for further work.

2. Related work

Connected production profoundly changes the scope of key manufacturing operations, including intralogistics. To assess current work in this area, the following sections analyze relevant literature regarding functional aims and requirements for performance measurement in this domain from the viewpoint of introducing key Industry 4.0 technologies and data process chains linked to performance management. In doing so this section discusses related work on performance measurement in intralogistics, including relevant KPIs, integration of IoT and CPS in this field of manufacturing operations, and outlines implications for relevant data process workflows.

2.1. Performance measurement in intralogistics

Performance measurement aims to provide information through the determination of key performance indicators (KPIs). Intralogistics is part of operations management and, therefore, concepts related to KPIs in manufacturing operations, as defined in the ISO 22400 family of standards, are applicable. This classifies KPIs in different categories, depending on their purpose of use. For example, KPIs may target performance measurements in terms of cost, time, quality, flexibility and sustainability. Furthermore, they can be relevant to different categories of operations, such as production, inventory handling, quality assurance, maintenance, and more.

Among KPI targets in manufacturing operations, intralogistics is an important contributor to several aspects of overall manufacturing performance, and especially throughput, utilization, equipment effectiveness, but also to non–functional metrics, for example sustainability and energy consumption. Related work has looked upon how measurable KPIs are used to quantify the operating performance and thus, enable its monitoring (Hwang, Lee, Park, & Chang, 2017). The lack of such performance measurement systems, or the use of poorly developed ones, cause a lack of understanding on how companies could improve their logistics systems (Granlund & Wiktorsson, 2014). This highlights the difficulty of providing relevant performance information of internal logistics systems in a comprehensive and effective way to drive improvements.

The selection of appropriate KPIs for intralogistics requires a proper understanding of the fundamentals of the studied process and the consideration of relevant standards, such as the ISO 22400 family of standards (Hwang et al., 2017). Accordingly, an overview of typical KPIs in intralogistics, alongside the required data to calculate them, is shown in Table 1 (based on Gudehus & Kotzab, 2012; Hwang et al., 2017; Pei, Zhao, Zhang, & Guo, 2019). These KPIs target the quantification of several aspects of performance, such as throughput, effectiveness, availability, and energy efficiency. While the first six indicators are used to evaluate the operational performance, the seventh and eight indicators are relevant to the uptime. The ninth indicator provides information about sustainability. Finally, the last indicator represents the overall equipment effectiveness (OEE), which is one of the most important KPIs in the area of manufacturing operations (Hwang et al., 2017).

Table 1
KPIs in intralogistics.

No.	KPIs	Required data
1	TH: Throughput [units/s] TH = TQ / RT	TQ: Transported quantity [units] RT: Reference time [s]
2	CT: Cycle Time [s] CT = TL / TS	TL: Length of transport way [m] TS: Transport speed [m/s]
3	TP: Transport Performance [kg/m] TP = (TQ / RL) × MG	TQ: Transported quantity [units] RL: Reference length [m] MG: Mass per good [kg/unit]
4	TrU: Transport Utilization [%] TrU = TH / TC × 100	TH: Throughput [units/s] TC: Transport capacity [units/s]
5	TiU: Time Utilization [%] TiU = ATT / OPT × 100	ATT: Actual transporting time [s] OPT: Operation time [s]
6	EF: Effectiveness [%] EF = ATT / PTT × 100	ATT: Actual transporting time [s] PTT: Planned transporting time [s]
7	AV: Availability [%] AV = ATT / PBT × 100	ATT: Actual transporting time [s] PBT: Planned busy time [s]
8	RE: Reliability [%] RE = ABT / (ABT + ADT) × 100	ABT: Actual busy time [s] ADT: Actual down time [s]
9	EE: Energy Efficiency [kWh/unit] EE = EC / TQ	EC: Energy consumption [kWh] TQ: Transported quantity [units]
10	OEE: Overall Equipment Effectiveness [%] OEE = EF × AV × QU / 100	EF: Effectiveness [%] AV: Availability [%] QU: Quality [%]

Having considered appropriate KPIs for effective performance monitoring of an internal logistics system, the focus shifts on the nature of the data generation processes needed for their estimation, and the added value offered by the necessary data processing chains for such measurements.

2.2. IoT and CPS in intralogistics

While digitization expands to all business domains, the concept of Industry 4.0, known as the fourth industrial revolution, specifically refers to manufacturing digitalization enabled by a multitude of emerging and advanced technologies, including Internet of Things (IoT), big data, and cloud computing (Colombo, Karnouskos, Shi, Yin, & Kaynak, 2016; Gilchrist, 2016). IoT represents the connection of physical objects with the digital world through a network that enables them to interact with each other and the physical environment, composing the concept of a Cyber-Physical System (CPS) and in particular Cyber Physical Production System (CPPS) in a manufacturing environment (Cardin, 2019). These objects are equipped with sensors and actuators to sense and manipulate their environment (Macaulay et al., 2015; Tu, Lim, & Yang, 2018), a capability that is associated with intelligent objects. Two different types of such objects can be distinguished. The first includes objects with integrated data processing and decision-making tools (decentralized intelligence), whereas the second includes objects where the smart data processing takes place on a remote platform (centralized intelligence) (Hribernik, Hans, Kramer, & Thoben, 2011). The need for interoperability between the digital and physical entities in a CPPS environment requires establishing appropriate mapping between them (Givehchi, Landsdorf, Simoens, & Colombo, 2017), often delivered through ontology – based modelling (Fumagali et al., 2018). In this way, the digital counterparts of the shop floor physical entities are enabled to exchange information with supervisory control and data aquisition systems (SCADA), human-machine interfaces (HMI), management end execution systems (MES), as well as with cloud monitoring services through appropriate industrial IoT gateways (Zolotová, Bundzel, & Lojka, 2015).

Several technologies related to IoT have been used in intralogistics, for example identification and sorting technologies to control the internal flow of goods (Gilchrist, 2016; Hribernik et al., 2011). Improved operational efficiency, transparency and enhanced customer experience are some of the typical benefits of IoT in intralogistics. Preventive maintenance is another example of employing IoT in intralogistics, wherein monitoring indicators for detecting an emerging malfunction and notifying responsible staff if the values exceed acceptable levels enables early fault anticipation and downtime reduction (Macaulay et al., 2015).

While IoT focuses on objects connectivity, a CPS represents the twining of a physical with a digital system and allows interactions between the physical and digital realm (Marwedel & Engel, 2016; Tu et al., 2018). CPS – based intralogistics implement such twining in production environments (Yan, Zhang, & Fu, 2019) and contribute towards addressing some of the key challenges relevant to the integration of internal logistics within the overall production. The challenges refer to the complexity of the data and information management, and the collaboration and capabilities exploitation of the physical production assets, so as to achieve higher production efficiency (Hohmann & Posselt, 2019). The ubiquitous nature of data and services in CPS solutions constitutes the critical enabler for capabilities exploitation and synchronization (Luo, Wang, Kong, Lu, & Qu, 2017; Tu et al., 2018). However, increased connectivity results also in scaled up requirements for the data workflows and processing, needed to drive decisions in intralogistics. An emerging approach to handle such complexity is through context aware CPS systems (Perera et al., 2014; Scholze & Barata, 2016).

2.3. The data value chain and context awareness in intralogistics

A data value chain describes the process of transforming raw data (lowest value) into applied knowledge (highest value) (Fig. 1). The chain starts with acquiring data from a system, which includes generating, collecting and storing data. This is followed by the data processing to extract valuable information. The third step involves analyzing this information by employing appropriate methods and tools to gain knowledge about the system. The application of the gained knowledge is performed in the final step and can lead, for example, to improved decision-making (Curry, 2016; Miller & Mork, 2013).

Whereas the above is a process-centric view, a data-centric one can be illustrated as in Fig. 2 as a DIKW pyramid, comprising the data, information, knowledge, and wisdom hierarchy. Baškarada and Koronios (2013) as well as Rowley (2007) describe data as providing only limited value to the user. It is typically generated by sensors and represents the lowest level in the hierarchy. Processing that data enables extracting information that is described as structured and interpreted data. Some of the several definitions of knowledge in the literature express that new knowledge is gained through the understanding contextual information on existing knowledge. Wisdom represents the top level of the DIKW pyramid and is described as the ability to apply the gained knowledge to solve arising problems. A similar view of data value chains is frequently adopted in the literature (Baškarada & Koronios, 2013; Rowley, 2007).

With the increasing integration of connectivity in manufacturing environments, intralogistics can also adopt relevant technologies to enhance capabilities for monitoring, controlling, and optimizing performance. The incorporation of contextual information about the situation under which the physical system is operating constitutes a key factor in addressing the increasing complexity of the aforementioned activities in order to improve the effectiveness of data value chains, an approach that is broadly known as context-aware computing (Perera et al., 2014, Scholze & Barata, 2016). When considering IoT enabled systems, context awareness facilitates handling the volume and complexity of generated data, as it supports the identification of data relevant to a specific situation. Analyzing such contextual information results in a better understanding of the physical system and thus, in gaining more actionable knowledge (Perera et al., 2014; Scholze & Barata, 2016). However, for context modelling to be effective, it needs to further detail the abstract higher level context to application domain–specific characteristics (domain-specific context). Therefore, there is a need to develop context models for applications in intralogistics and to this end ontological approaches for production systems are being extended to include internal logistics systems domain ontologies (Negri, Perotti, Fumagalli, Marchet, & Garetti, 2017). Nonetheless, to make such context modelling actionable, there is a need to introduce context-driven data processing and analytics. Although aspects of IoT-enabled data workflows have been used in intralogistics in the past, the realization of IoT-driven analytics is a relatively new approach to drive the optimization of internal logistics systems in terms of operational performance, uptime and sustainability. While IoT-enabled data value chains deal with the acquisition, transmission, and effective transformation of raw data into applied knowledge, it is their inclusion within CPS that can deliver their outcomes in intralogistics practice and further work is needed to this end.

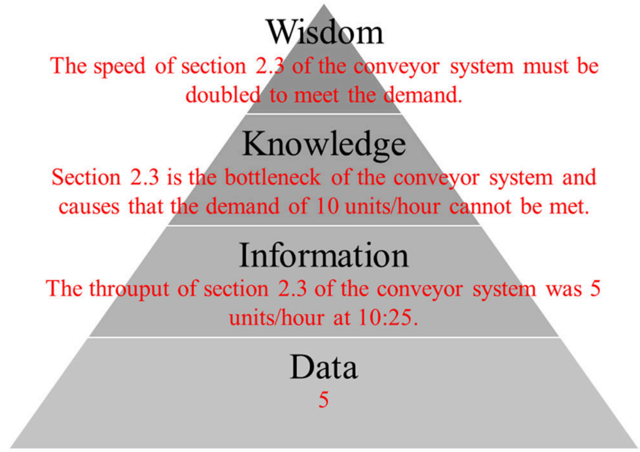

Fig. 2. DIKW-pyramid.

3. CPS and intralogistics context

This section introduces a conceptual model of a CPS in intralogistics aimed at enhancing performance monitoring practice. It includes the utilization of key Industry 4.0 technologies to create and utilize relevant data processing chains and a context model for intralogistics, as a driver to making such data process chains more effective.

3.1. Conceptual model of a CPS in intralogistics

There is a growing body of literature covering technology, architectures, and industrial applications of CPS (Colombo et al., 2016; Gilchrist, 2016; Marwedel & Engel, 2016; Lee et al., 2015; Schuh, Bernardy, Zeller, & Stich, 2017; Zolotová et al., 2015). Fig. 3 shows an overall conceptual model of such a CPS, adapted from Gilchrist (2016).

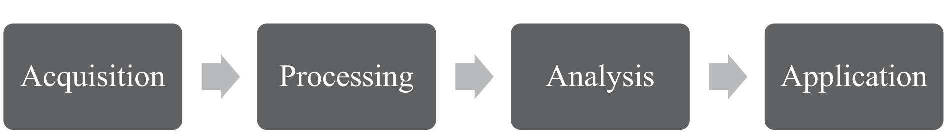

Fig. 1. Simplified data value chain.

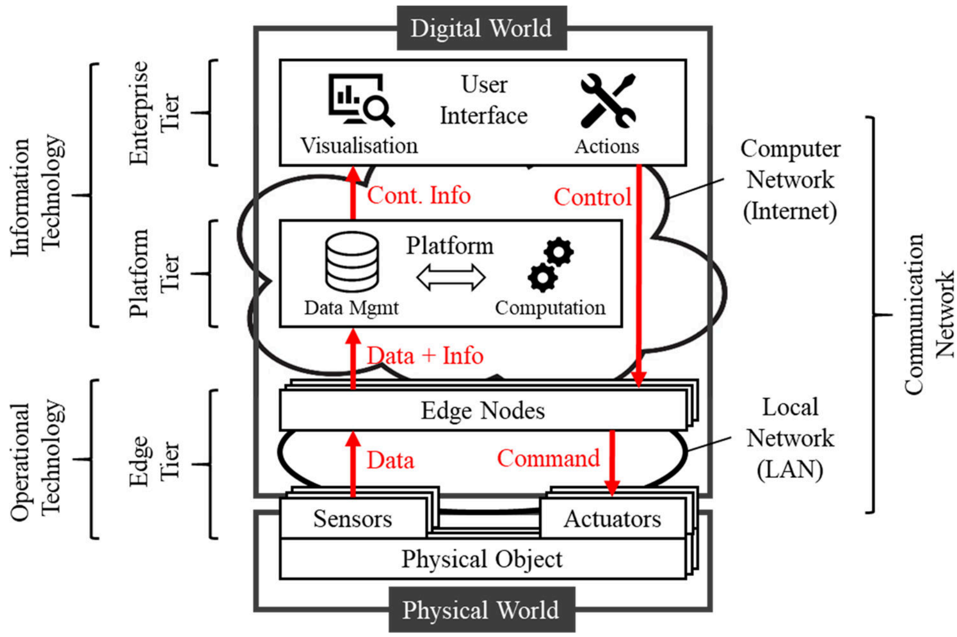

Fig. 3. Conceptual model of a CPS (based on Gilchrist, 2016).

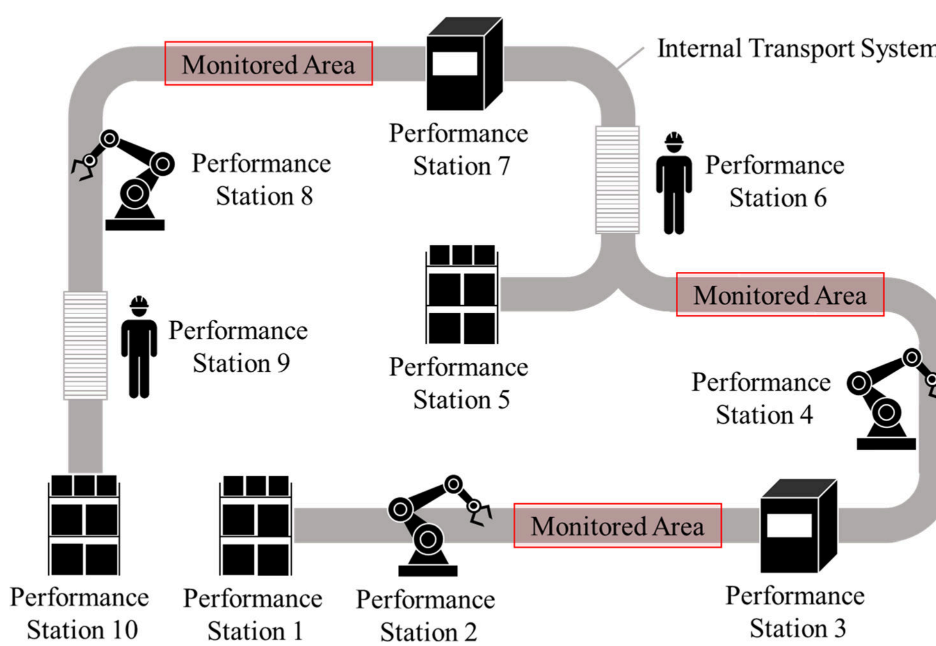

Fig. 4. Concept of performance monitoring in intralogistics.

The basic structure is also in line with similar proposed architectures, for example regarding real-time monitoring of assembly lines (Syafrudin, Alfian, Fitriyani, & Rhee, 2018), IoT-enabled CPS for production logistics (Tu et al., 2018; Yan et al. (2019) or more broadly industrial automation CPS (Leitão, Colombo, & Karnouskos, 2016; Colombo et al., 2016; Panetto, Iung, Ivanov, Weichhart, & Wang, 2019). Adopting a three-tier architecture, physical objects equipped with sensors and actuators compose the lower or edge tier. Network connectivity establishes data and command communications between the edge nodes but also between the edge tier and higher level tiers. Edge nodes represent control units and vary from single-board computers, programmable logical controls (PLC) to desktop computers. They manage the connected sensors and actuators as well as perform a first level of data processing. This enables a significant reduction in the volume and bandwidth required for the data to be transmitted to upper tiers. A platform receives data from several edge nodes via the network and is responsible for their transformation, storage, and further processing over the cloud. The final or enterprise tier provides the main user interfaces, including applications to vizualize information to enable gaining potentially new knowledge. Decision making arises from the application of knowledge and may lead to taking corrective or preventive actions that might directly affect the edge tier and consequently the physical world.

The basic view of a CPS illustrated in Fig. 3 is also applicable to intralogistics, by considering the actual physical entities typically present in this domain. Internal logistics systems generally consist of performance stations, such as machines, storing areas, and commissioning systems that are connected by several types of internal transportation systems. While performance stations typically have distinctive and product-specific cycle times, different goods might follow individual paths through the internal logistics system (Gudehus & Kotzab, 2012). Current internal logistics systems exhibit varying levels of complexity, with the fairly complex ones already bringing the abilities of human operators to optimize them to reach their limits (Gilchrist, 2016). While physical complexity can be daunting in large scale system, the benefit of implementing a CPS for performance monitoring is that it translates the physical complexity into a digital one, making it possible to handle it with digital means. This in turn facilitates the management and processing of acquired data, which can lead to the identification of bottlenecks, malfunctions, or critical paths, and make the measurements and calculations needed for KPI-based performance monitoring more manageable. Hence, monitoring systems as part of CPS are important enablers for more efficient intralogistics (Pei et al., 2019).

Fig. 4 illustrates a simple example of an internal logistics system including ten performance stations, where three areas of the transport system are marked as being monitored through different sensors. While the number and position of monitored areas strongly depend on the actual internal logistics system as well as the experience of system designers, it is recommended to focus on critical spots to enable a cost-effective but comprehensive identification of optimization potential. Thus, by monitoring a reduced set of physical assets in an intralogistics infrastructure, it is possible to indirectly infer performance at different locations, making possible to identify sources of disruption, even if the source of the bottleneck is not directly monitored. The analysis of KPIs identified in Section 2.1, referring to operational performance, uptime and sustainability, can lead to further insights about contributing or limiting factors to overall performance.

More effective data process chain management can be achieved by the incorporation of context-aware computing, considering the specific operating situation of the logistics system. To this end, a high-level assessment of context in intralogistics is introduced in the next section.

3.2. Context categories in intralogistics

Intralogistics operations need to take into account the physical capabilities of the infrastructure, the nature of the transported goods, the human operators and the surrounding environment, as well as the business requirements for internal logistics, while also considering physical, normative, and technology constraints. These are the key factors that compose the context of intralogistics operations and decision making, and are illustrated in Fig. 5 as six broad context categories, with each category further encompassing more detailed characteristics.

Order. The business context is provided through the order context, which is either internal or external. Every order involves a customer who requires the transportation of physical goods from the start point to the end point within a specific time frame. Furthermore, each order has a specific priority. The related physical goods can differ in several areas such as the type, cost, quantity, physical properties, content and priority.

Physical goods. These may include raw materials, components, assemblies, as well as their relationship to an order, along with the relevant priority, availability, handling constraints or guidelines, but also information about required quantities and physical properties.

Transport. In order to perform the transportation of these goods effectively, a transport system is essential. This can consist of different elements, such as conveyors, while information about the layout, capacity, specific loading inputs, and throughput enable the evaluation of the internal logistics system performance. The transportation part of intralogistics incurs costs, which also need to be assessed.

Human. Human operators are still needed for some tasks. Human resources may have different roles and responsibilities, as well as different costs associated with them.

Environment. The surrounding environment plays an important role. Environmental constraints are non-functional and may include safety, comfort, networking and interference.

Service. The service represents a higher-level business task, performed according to certain specifications and constitutes a concrete part of the intralogistics processes.

Among the above elements, there can be context aspects which may need to be taken into account in more than one high level context categories. Sensor readings enable providing information of the internal logistics system to other subsystems and human operators, which may be relevant to the operational status of an order, a transportation subsystem, or the environment. Costs considerations may be relevant to human resources, order materials, energy consumption, or physical transportation assets. Combining the information about the investment and operational cost of the transport system with the labor cost allows detailed cost estimations. Having created a general context model for

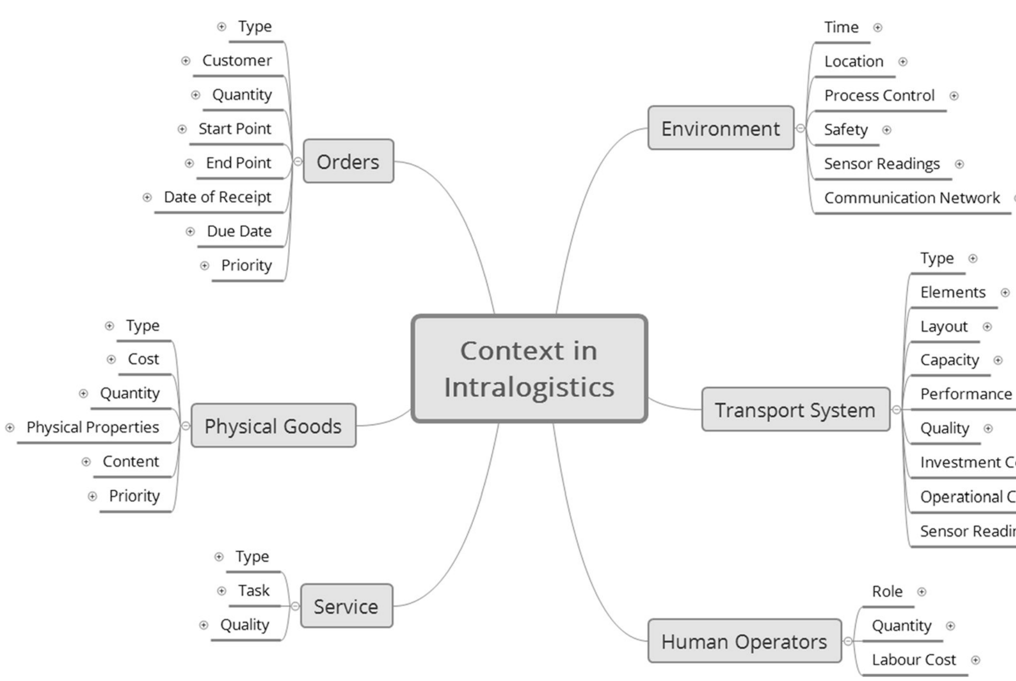

Fig. 5. General context categories in intralogistics.

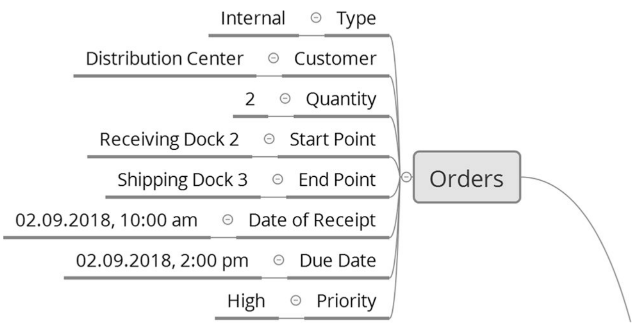

Fig. 6. Intralogistics order context category and application case detailed context.

intralogistics of such level of abstraction does not yet make it actionable. To become so, it needs to be grounded to an application domain-specific context. For example, Fig. 6 visualizes the category "orders" for a sample use case.

Identifying characteristics of specific situations, under which an internal logistics system is operating, enables an improved understanding of dependencies between the involved categories. This in turn offers a better basis upon which to design risk mitigation and plan for optimization opportunities. For instance, the occurrence of extreme bottlenecks in case the order quantity of a specific good exceeds a particular level, may provide actionable knowledge to trigger either a redesign of the internal logistics system, or the customer order management and prioritization process. Applying this knowledge on the actual root cause may therefore result in an improved intralogistics process.

4. Development of intralogistics CPS demonstrator

This section presents the development of an instantiation of an intralogistics CPS through a laboratory scale demonstrator application case. The aim is to bring together some of the key elements of the conceptual approach on a physical intralogistics infrastructure to demonstrate a case of IoT-driven KPI analytics for performance monitoring. Although the demonstrator represents a specific instance, it is indicative of other possibilities.

4.1. Demonstrator set up

The first step to develop the CPS demonstrator was the definition of a representative use case. This paper focuses on an existing university lab conveyor testbed. The overall layout and positions of the various conveyors are shown in Fig. 7, showing also the two cyclic journeys of 27.97 m (circle one) and 29.90 m (circle two) total length that transported goods (parcels) can follow. The testbed includes many different conveyor types, which can be employed in practice, and is therefore a fairly representative use case in intralogistics. The conveyor types characteristics are detailed in Table 2.

The actual conveyor system, controlled through PLC (Siemens SIMATIC S7-300) and transferring parcels, is shown in Fig. 8.

Having focused on this representative testbed in intralogistics, the next step was to define and deploy a system that is capable of acquiring data that can be employed to estimate the testbed performance. Specifically, the interest lies with calculating eight KPIs relevant to the operational performance, uptime, sustainability and OEE (Table 3), which belong to two groups. The first group contains all KPIs that are related to single units (throughput, cycle time) or are directly dependent on the throughput (transport performance, transport utilization). The second group contains all KPIs that are related to a specific period of time (time utilization, effectiveness, availability, overall equipment effectiveness).

There are various different options of sensors which could be employed for such measurements. For example, a simple choice would be to incorporate position/presence sensors. However, the choice made was to employ vision cameras, as these can be very versatile and a choice consistent with easily sourced, installed, and managed hardware. The structure of the data acquisition system is illustrated in Fig. 9.

The conveyor testbed is the physical infrastructure of objects providing the source for the measurements. While a vision camera is positioned at a specific location off the conveyor to capture the movement of parcels, a low-cost general purpose IoT device was employed as edge node, i.e. a Raspberry Pi 3 Model B. The captured video is then processed through a Simulink model which either runs on a connected laptop or on the raspberry pi. This model detects moving parcels and classifies them according to their color (red, green, blue), sending the outcomes to the cloud through two ThingSpeak (thingspeak.com – the platform for Matlab IoT analytics) channels. ThingSpeak was employed as the cloud platform for transferring and visualizing the monitored performance as it offered the required basic functionality while being free to use. However, many other platforms could be employed instead, including commercial ones, such as ThingWorx, IBM Watson, AWS IoT, ThinksBoard, and Kaa (Hassan, 2018). The video processing takes place on board at the edge node, making it possible to transmit only numbers, rather than the acquired video images to the cloud, reducing the need for data transmission bandwidth. Distributing analytics tasks between the edge and the cloud is a design choice that is worth investing on, depending on the nature of the targeted application. Upon data receipt, specific MATLAB programs are executed for KPIs estimation. Furthermore, a user interface running on a connected laptop enables to manually enter initialization data (parameters that are necessary to calculate additional KPIs but cannot be extracted from the video), as well as to initiate or stop the Simulink model. This system represents a simple solution via low-cost components to realize the required data acquisition. Using a webcam results in a flexible CPS that can be implemented in any type of conveyor system with limited adaptation. The mobility of the camera position enables simple changes of the monitored area. The used Simulink model can be organized into six areas as illustrated in Fig. 10.

Starting with capturing the video (1), the detection and count of moving objects (2) as well as red, green and blue objects (3) represents the extraction of the relevant data. An additional visualization component is added to support testing and calibration purposes (4). Furthermore, all values of the required parameters to calculate additional KPIs are read (5) and subsequently sent to two ThingSpeak channels (group A) together with the current count of moving and colored parcels and are presented as a visualization dashboard (6). The time between sending new data to the channels is given by the user interface through the snapshot time. The modules of the Simulink model are: 1: Video capture; 2: Detection of moving objects; 3: Detection of red, green and blue objects; 4: Visualization of detected objects and results; 5: Parameters of transported components; 6: IoT board sending data to ThingSpeak channels.

4.2. Performance monitoring demonstrator testing

All data sent from the Simulink model are received and processed through the group A ThingSpeak channels – a second group is employed for the KPIs and is discussed later.

Table 4 provides an overview of this data set, consisting of sixteen parameters. The demonstrator is capable of estimating eight KPIs, shown in Table 3. The data processing is performed through MATLAB programs implemented in the group A ThingSpeak channels. In order to integrate the data processing and information visualization system with the data acquisition system, apps provided by ThingSpeak (Visualization app, Analysis app, TimeControl app, React app) are used. The last task of the demonstrator is KPIs vizualisation via two additional ThingSpeak channels (group B). While the first channel comprises all KPIs that are part of group one including throughput, cycle time,

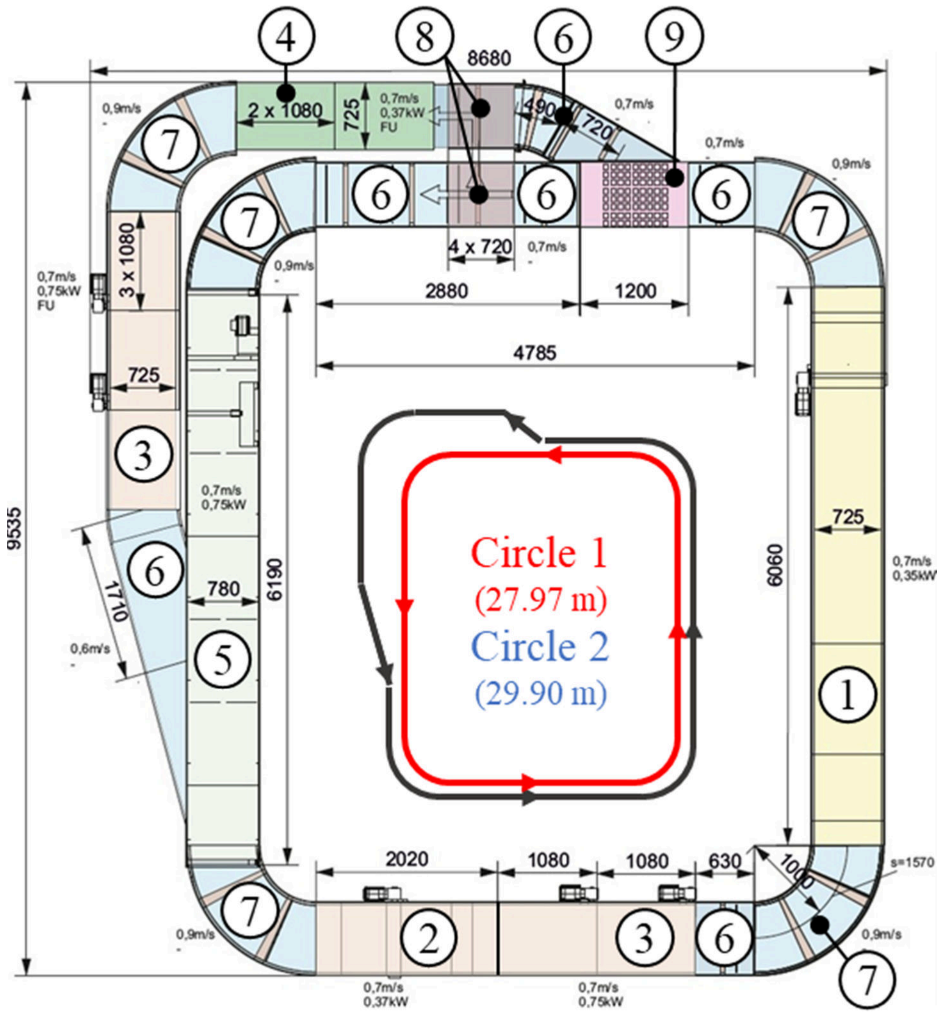

Fig. 7. Layout of the conveyor system.

Table 2
Testbed Conveyor Types.

Pos.	Type	Mechanical Drive	Length	Speed
1	Belt conveyor (roller bed)	External belt drive	1 × 6.06 m	0.7 m/s
2	Belt conveyor (slider bed)	External belt drive	1 × 2.02 m	0.7 m/s
3	Belt conveyor (slider bed)	Direct drive at return pulley	5 × 1.08 m	0.7 m/s
4	Link belt conveyor	Direct drive at return pulley	2 × 1.08 m	0.7 m/s
5	Roller conveyor	Central belt drive	1 × 6.19 m	0.7 m/s
6	Roller conveyor	Single roller drive, connected via belts	1 × 1.44 m, 2 × 0.72 m, 1 × 0.63 m, 1 × 1.71 m	0.7 m/s, 0.7 m/s, 0.7 m/s, 0.6 m/s
7	Roller conveyor (curved)	Single roller drive, connected via belts	5 × 1.57 m	0.9 m/s
8	Belt diverter	External drive	2 × 0.72 m	0.7 m/s
9	Roller Switch	External drive	1 × 1.20 m	0.7 m/s

transport performance and transport utilization, the second channel covers all KPIs that are part of group two including the time utilization, effectiveness, availability and the overall equipment effectiveness. Sample visualization of the throughput is shown in Fig. 11.

4.3. Demonstrator testing

The final step was the testing of the demonstrator functionality. For this a case study was carried out with red, green and blue parcels transported along circle one for 260 s in a random order. The chosen values of the parameters for the Simulink model represented a realistic case in intralogistics. Table 5 lists the involved steps of the test run, whereas the time specifications are absolute and identical with the time provided by the Simulink model. It is assumed that each red parcel contains one item of product A, each green contains one item of product B and each blue one piece of product C. This stands as a functional test, demonstrating how a legacy internal logistics system can be upgraded with performance monitoring capabilities via inexpensive IoT components.

Using the throughput based on a manual count as baseline data, the remainder of this section provides an example of obtained results when comparing the manually computed throughput with the throughput determined via the CPS. Most observed deviations (though small) are due to the sampling limitations of the employed ThingsSpeak channels and the term 'lost point' is employed to denote a 'missed event', wherein in this case event constitutes the transportation of a parcel. However, such sampling limitations could easily be overcome as even simple solutions with widely accepted connectivity protocols, such as MQTT, would enable a relatively small roundtrip latency of less than 50 ms within the same continent and 300 ms between continents with a standard deviation of 20 ms (Ferrari, Sisinni, Brandão, & Rocha, 2017). Fig. 12 shows the throughput based on the manual count of parcels in

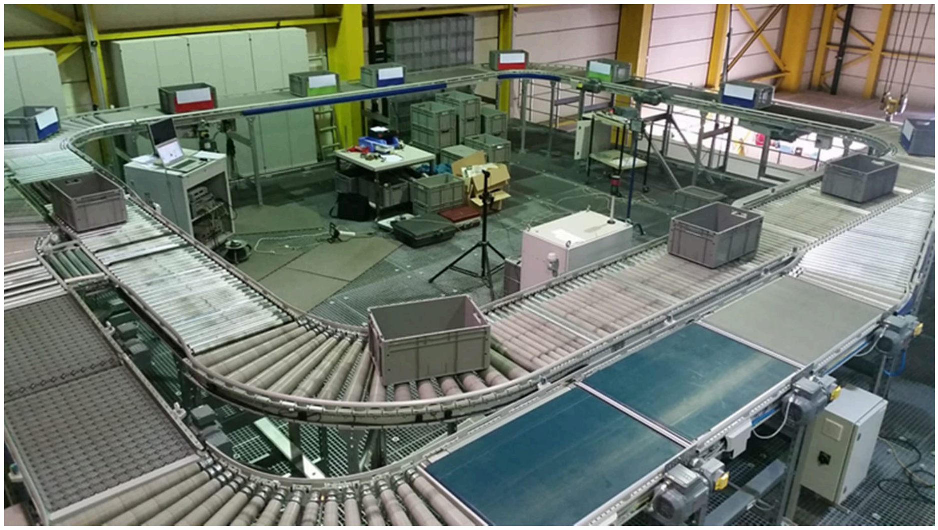

Fig. 8. Real world conveyor system.

Table 3
Targeted Key Performance Indicators.

No.	KPIs	Group
1	TH: Throughput [units/s]	1
2	CT: Cycle Time [s]	1
3	TP: Transport Performance [kg/m]	1
4	TrU: Transport Utilization [%]	1
5	TiU: Time Utilization [%]	2
6	EF: Effectiveness [%]	2
7	AV: Availability [%]	2
8	OEE: Overall Equipment Effectiveness [%]	2

grey and the throughput determined via the CPS demonstrator in red.

The comparison identified an increasing time displacement between the corresponding data points. This is caused as the time between sending new data from the Simulink model to the ThingSpeak channels (group A) is not constant due to random deviations. While each positive or negative deviation from the set snapshot time contributes to a cumulative time displacement, several tests have shown that most of these deviations are limited. In the presented case the small deviation between the two areas correspond to a single missed point out of 54, with an average displacement time of 2.5 s (of limited importance when the interest is about throughput) and an overall deviation between actual and estimated throughput at 3.16%. This is acceptable performance considering that the CPS demonstrator only involved low-cost components and non-fixed but movable cameras.

5. Conclusion

This paper introduced a conceptual approach for CPS in intralogistics, implemented through a CPS demonstrator for performance monitoring on a real conveyor belt testbed. This demonstrator offers a small-scale realization of a data process chain, from data generation to performance parameters estimation and visualization. The developed demonstrator serves as a small scale implementation of the concept of IoT-driven CPS system for performance monitoring analytics in intralogistics, which can be applicable to larger scale installations. The direct key benefit of introducing IoT-driven performance monitoring is linked to upgrading legacy production environments into CPS connected environments, able to produce, gather, and analyse operations data in an automated way, so as to drive performance improvements (Orellana & Torres, 2019). The tangible outcome for internal logistics within such an environment is to establish end to end transparency throughout the internal logistics process chain and translate this to mechanisms for performance monitoring and enhancement.

Ensuring appropriate synchronization and efficient collaboration

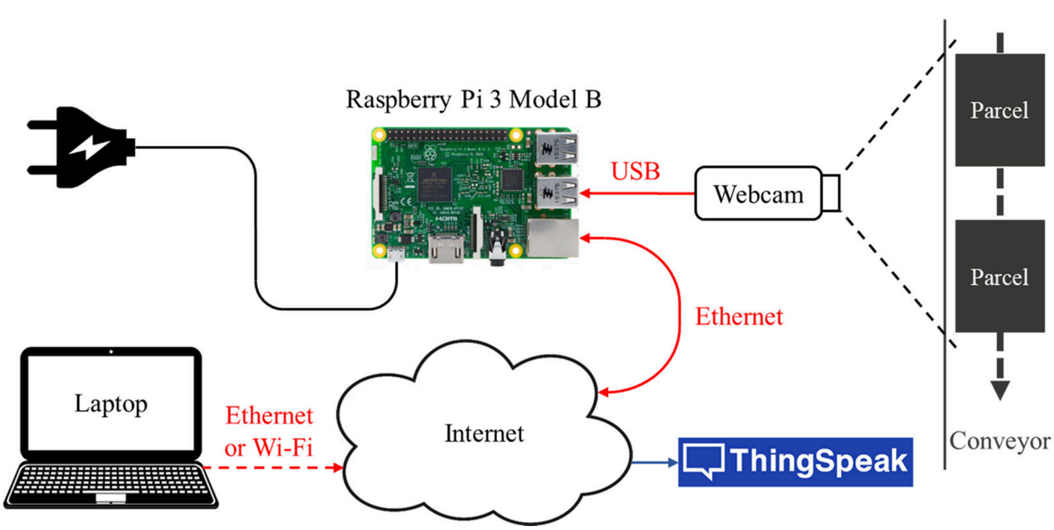

Fig. 9. Structure of the data acquisition system.

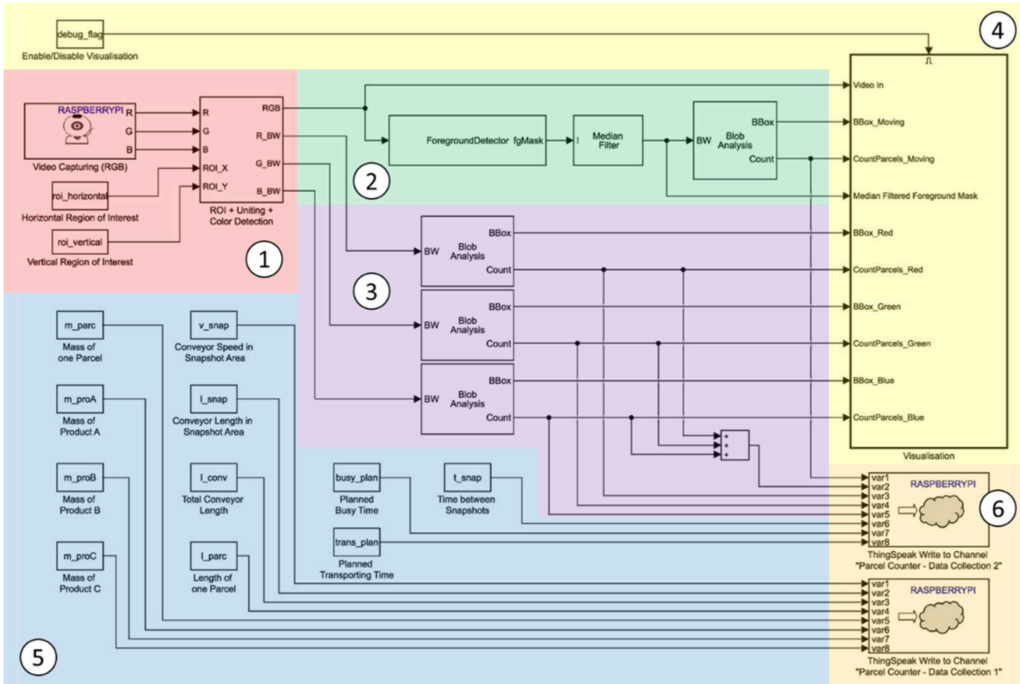

Fig. 10. Simulink model of the parcel counter.

Table 4
Data sent from the Simulink Model.

No.	Data	Source
1	Speed of the conveyor system in the snapshot area [m/s]	Entered manually
2	Length of the conveyor system in the snapshot area [m]	Entered manually
3	Total length of the conveyor system [m]	Entered manually
4	Length of one parcel [m]	Entered manually
5	Mass of one parcel [kg]	Entered manually
6	Mass of product A [kg]	Entered manually
7	Mass of product B [kg]	Entered manually
8	Mass of product C [kg]	Entered manually
9	Planned busy time as percentage of the operation time [%]	Entered manually
10	Planned transporting time as percentage of the planned busy time [%]	Entered manually
11	Snapshot time [s]	User interface
12	Count of moving parcels [units]	CPS demonstrator
13	Count of colored parcels [units]	CPS demonstrator
14	Count of red parcels [units]	CPS demonstrator
15	Count of green parcels [units]	CPS demonstrator
16	Count of blue parcels [units]	CPS demonstrator

and capabilities exploitation of the physical production assets remains an issue for further research (Hohmann & Posselt, 2019). Significant challenges still remain regarding the practical uptake of such technology upgrades (Tu et al., 2018). The management of data complexity and the introduction of interoperability mechanisms at the physical, process, and business layer in production environments both require further research (Panetto et al., 2019). Context information management constitutes a valid mechanism towards interoperable IoT-enabled systems (Perera et al., 2014) and context-aware mechanisms in intralogistics are needed to improve the effectiveness of the involved data value chains. The data acquisition system of the developed CPS demonstrator represents a simple and inexpensive solution as it employs low-cost hardware-components. Using a webcam results in a flexible CPS that can be implemented in other types of conveyor systems with little adaptation. This is just an example of how future operators can be assisted in their work environments with context-specific information

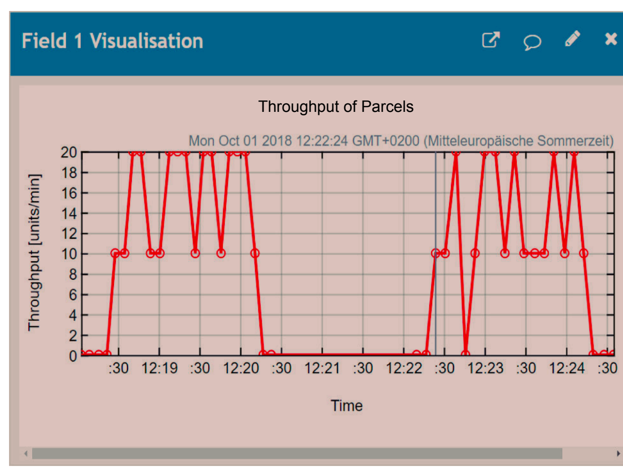

Fig. 11. Sample vizualization at a thingspeak channel – updated throughput.

Table 5
Steps of the performed test.

Step	Time [s]	Task
0	–	Simulink model and conveyor system are not running.
1	–	Start running the Simulink model on the laptop with the following parameters: 1. Conveyor speed in snapshot area = 0.7 m/s 2. Conveyor length in snapshot area = 3.25 m 3. Total length of conveyor system = 27.97 m 4. Length of one parcel = 0.5 m 5. Mass of one parcel = 1 kg 6. Mass of product A = 4 kg 7. Mass of product B = 8 kg 8. Mass of product C = 9 kg 9. Snapshot time = 5 s (calculated by an active element within the user interface) 10. Planned busy time = 85% 11. Planned transporting time = 90%
2	5	Start running the conveyor system.
3	265	Stop running the Simulink model and the conveyor system.

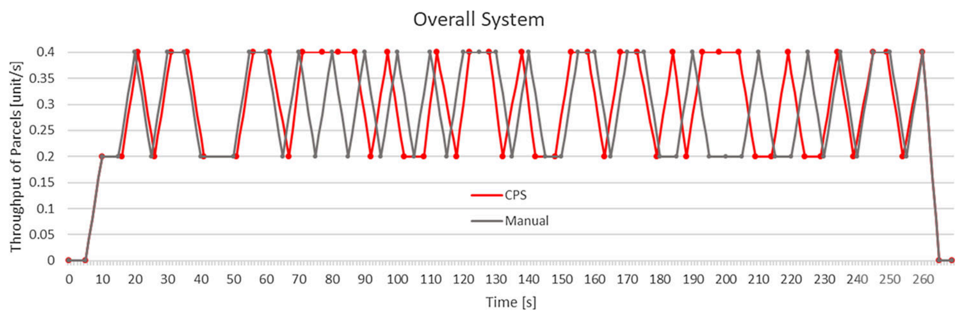

Fig. 12. Testing results of the overall system.

so as to focus their attention and effort on undertaking higher-value activities (Emmanouilidis et al., 2019). Identifying the characteristics of specific situations enables a better understanding of the internal logistics system and thus leads to more effective knowledge and insights acquisition. This is indeed among the key expectations in relation to the impact of Industry 4.0 technologies to job profiles, i.e. a switching from low-skilled and routine activities to ones that require higher skills or cognitive involvement from human operators in such environments (Zolotova et al., 2018). Although the presented demonstrator offers limited scope for context analysis, future work that targets systems of higher complexity would be required to implement effective context modelling and reasoning, which can also be exploited to drive context-adaptive views of performance information, raising attention to emerging context-relevant and higher priority issues. This would be a natural next step and aim for further research, and would be necessary in order to produce industrially relevant solutions. Such solutions could aim at optimizing internal logistics systems in terms of operational performance, uptime and sustainability through IoT-driven analytics.

References

Baškarada, S., & Koronios, A. (2013). Data, information, knowledge, wisdom (DIKW): A semiotic theoretical and empirical exploration of the hierarchy and its quality dimension. *Australasian Journal of Information Systems, 18*(1), 5–24.

Bode, W., & Preuß, R. (2005). *Comprehensive introduction to Intralogistics.* Norderstedt: Books on Demand.

Cardin, O. (2019). Classification of cyber-physical production systems applications: Proposition of an analysis framework. *Computers in Industry, 104*, 11–21. https://doi.org/10.1016/j.compind.2018.10.002.

Colombo, A. W., Karnouskos, S., Shi, Y., Yin, S., & Kaynak, O. (2016). Industrial cyber-physical systems. *Proceedings of the IEEE, 104*(5), 899–903.

Curry, E. (2016). The Big Data Value Chain: Definitions, Concepts, and Theoretical Approaches. In J. Cavanillas, E. Curry, & W. Wahlster (Eds.). *New Horizons for a Data-Driven Economy* (pp. 29–38). Switzerland: Springer.

Emmanouilidis, C., Pistofidis, P., Bertoncelj, L., Katsouros, V., Fournaris, A., Koulamas, C., & Ruiz-Carcel, C. (2019). Enabling the human in the loop: Linked data and knowledge in industrial cyber-physical systems. *Annual Reviews in Control, 47*, 249–265. https://doi.org/10.1016/j.arcontrol.2019.03.004 (Elsevier).

Ferrari, P., Sisinni, E., Brandão, D. & Rocha, M. (2017). Evaluation of communication latency in industrial IoT applications. 2017 IEEE International Workshop on Measurement and Networking (M&N). , September 27-29, Naples, Italy: IEEE.

Fritz, M. (2016). Beitrag zur Simulation des Bewegungsverhaltens von Stückgütern im Pulk im Kontext der Vereinzelung. Graz: Technische Universität Graz, Dissertation.

Fumagalli, L., Negri, E., Severa, O., Balda, P., & Rondi, E. (2018). Distributed control via modularized CPS architecture Lessons learnt from an industrial case study. *IFAC-PapersOnLine, 51*(11), 803–808. https://doi.org/10.1016/j.ifacol.2018.08.417.

Gilchrist, A. (2016). *Industry 4.0: The Industrial Internet of Things.* Thailand: Apress.

Givehchi, O., Landsdorf, K., Simoens, P., & Colombo, A. W. (2017). Interoperability for industrial cyber-physical systems: An approach for legacy systems. *IEEE Transactions on Industrial Informatics, 13*(6), 3370–3378. https://doi.org/10.1109/TII.2017.2740434.

Granlund, A., & Wiktorsson, M. (2014). Automation in internal logistics: Strategies and operational challenges. *International Journal of Logistics Systems and Management, 18*(4), 538–558.

Gudehus, T., & Kotzab, H. (2012). *Comprehensive Logistics.* Heidelberg: Springer.

Hassan, Q.F. (Ed), (2018), Internet of things A to Z: Technologies and Applications, Wiley-IEEE Press.

Hohmann, C., & Posselt, T. (2019). Design challenges for CPS-based service systems in industrial production and logistics. *International Journal of Computer Integrated Manufacturing, 32*(4–5), 329–339. https://doi.org/10.1080/0951192X.2018.1552795.

Hribernik, K., Hans, C., Kramer, C., & Thoben, K. (2011). A Service-oriented, Semantic Approach to Data Integration for an Internet of Things Supporting Autonomous Cooperating Logistics Processes. In D. Uckelmann, M. Harrison, & F. Michahelles (Eds.). *Architecting the Internet of Things* (pp. 131–158). Heidelberg: Springer.

Hwang, G., Lee, J., Park, J., & Chang, T. (2017). Developing performance measurement system for Internet of Things and smart factory environment. *International Journal of Production Research, 55*(9), 2590–2602. https://doi.org/10.1080/00207543.2016.1245883.

Lee, J., Bagheri, B., & Kao, H. A. (2015). A cyber-physical systems architecture for industry 4.0-based manufacturing systems. *Manufacturing Letters, 3*, 18–23. https://doi.org/10.1016/j.mfglet.2014.12.001.

Leitão, P., Colombo, A. W., & Karnouskos, S. (2016). Industrial automation based on cyber-physical systems technologies: Prototype implementations and challenges. *Computers in Industry, 81*, 11–25. https://doi.org/10.1016/j.compind.2015.08.004.

Luo, H., Wang, K., Kong, X. T. R., Lu, S., & Qu, T. (2017). Synchronized production and logistics via ubiquitous computing technology. *Robotics and Computer-Integrated Manufacturing, 45*, 99–115. https://doi.org/10.1016/j.rcim.2016.01.008.

Macaulay, J., Buckalew, L., & Chung, G. (2015). *Internet of Things in Logistics.* Troisdorf: DHL Trend Research.

Marwedel, P., & Engel, M. (2016). Cyber-Physical Systems: Opportunities, Challenges and (Some) Solution. In A. Guerrieri, V. Loscri, A. Rovella, & G. Fortino (Eds.). *Management of Cyber Physical Objects in the Future Internet of Things: Methods, Architectures and Applications* (pp. 1–30). Switzerland: Springer.

Miller, H. G., & Mork, P. (2013). From data to decisions: A value chain for big data. *IT Professional, 15*(1), 57–59. https://doi.org/10.1109/MITP.2013.11.

Negri, E., Perotti, S., Fumagalli, L., Marchet, G., & Garetti, M. (2017). Modelling internal logistics systems through ontologies. *Computers in Industry, 88*, 19–34. https://doi.org/10.1016/j.compind.2017.03.004.

Orellana, F., & Torres, R. (2019). From legacy-based factories to smart factories level 2 according to the industry 4.0. *International Journal of Computer Integrated Manufacturing, 32*(4–5), 441–451. https://doi.org/10.1080/0951192X.2019.1609702.

Panetto, H., Iung, B., Ivanov, D., Weichhart, G., & Wang, X. (2019). Challenges for the cyber-physical manufacturing enterprises of the future. *Annual Reviews in Control, 47*, 200–213. https://doi.org/10.1016/j.arcontrol.2019.02.002.

Pei, S., Zhao, J., Zhang, N., & Guo, M. (2019). Methodology on developing an assessment tool for intralogistics by considering cyber-physical production systems enabling technologies. *International Journal of Computer Integrated Manufacturing, 32*(4–5), 406–412. https://doi.org/10.1080/0951192X.2019.1605200.

Perera, C., Zaslavsky, A., Christen, P., & Georgakopoulos, D. (2014). Context aware computing for the internet of things: A survey. *IEEE Communications Surveys and Tutorials, 16*(1), 414–454. https://doi.org/10.1109/SURV.2013.042313.00197.

Rowley, J. (2007). The wisdom hierarchy: Representations of the DIKW hierarchy. *Journal of Information Science, 33*(2), 163–180.

Scholze, S., & Barata, J. (2016). Context Awareness for Flexible Manufacturing Systems Using Cyber Physical Approaches. In L.M. Camarinha-Matos, A.J. Falcão, N. Vafaei & S. Najdi (Eds.), Technological Innovation for Cyber-Physical Systems. 7th IFIP WG 5.5/SOCOLNET Advanced Doctoral Conference on Computing, Electrical and Industrial Systems, April 11–13, Costa de Caparica. Switzerland: Springer.

Schuh, G., Bernardy, A., Zeller, V. & Stich, V. (2017). New Requirement Analysis Approach for Cyber-Physical Systems in an Intralogistics Use Case. In L.M. Camarinha-Matos, H. Afsarmanesh & R. Fornasiero (Eds.), Collaboration in a Data-Rich World. 18th IFIP WG 5.5 Working Conference on Virtual Enterprises. September 18–20, Vicenza, Italy: Springer.

Syafrudin, M., Alfian, G., Fitriyani, N. L., & Rhee, J. (2018). Performance analysis of iot-based sensor, big data processing, and machine learning model for real-time monitoring system in automotive manufacturing. *Sensors, 18*(2946), 1–24. https://doi.org/10.3390/s18092946.

Tu, M., Lim, M., & Yang, M. F. (2018). Internet of things-based production logistics and supply chain system-Part 1: IoT-based cyber-physical system: A framework & evaluation. *Industrial Management & Data Systems, 118*(1), 96–9125. https://doi.org/10.1108/IMDS-11-2016-0503.

Yan, J., Zhang, M. & Fu, Z. (2019) An intralogistics-oriented Cyber-Physical System for workshop in the context of Industry 4.0. In: T.C. Jen, E. Akinlabi, P. Olubambi and C. Augbavboa (Eds.), Procedia Manufacturing 35. The 2nd International Conference on Sustainable Materials Processing and Manufacturing (SMPM), pp. 1178–1183, March 8–10, Sun City, South Africa: doi: 10.1016/j.promfg.2019.06.074.

Zolotová, I., Bundzel, M. & Lojka, T. (2015). Industry IoT Gateway for Cloud Connectivity. In S. Umeda, M. Nakano, H. Mizuyama, H. Hibino, D. Kiritsis and G. von Cieminski (Eds.), Advances in Production Management Systems: Innovative Production Management Towards Sustainable Growth. IFIP WG 5.7 International Conferenceon Advances in Production Management Systems (APMS), pp. 59-66, September 7–9, Tokyo, Japan: Springer. doi: 10.1007/978-3-319-22759-7_7.

Zolotová, I., Papcun, P., Kajáti, E., Miškuf, M., & Mocnej, J. (2018). Smart and cognitive solutions for Operator 4.0: Laboratory H-CPPS case studies. Computers and Industrial Engineering, in press, 105471. Doi: 10.1016/j.cie.2018.10.032.

2020-02-01

Cyber-physical systems for performance monitoring in production intralogistics

Mörth, O.

Elsevier

Mörth O, Emmanouilidis C, Hafner N, Schadler M. (2020) Cyber-physical systems for performance monitoring in production intralogistics. Computers and Industrial Engineering, Volume 142, April 2020, Article number 106333

https://doi.org/10.1016/j.cie.2020.106333